Is disequilibrium collaboration really conductive to catch-up in enabling technologies？

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Introduction

Technological progress can either widen the gap between those forging ahead and those falling behind, or it can be a catalyst that helps stragglers catch up. Great changes in the characteristics and circumstances of technological progress have been taking place. Without doubt, the processes for both forerunner and latecomer are becoming increasingly turbulent due to the rise of enabling technologies, such as artificial intelligence (AI), integrated circuit (IC), etc. How to grasp the catch-up opportunity window of these enabling technologies becomes a topic needs serious consideration.

Centrality are the most important indicators for investigating collaboration networks. According to the findings of Rowley and Behrens et al (2000), centrality indicates that an actor's position in a network has different strengths and weaknesses. However, there are some scholars considered that decreased centrality is also important for technology catch-up in specific conditions. Therefore, technology life cycle should be considered into exploring the relationship between centrality and technology innovation.

Facing the above confusions, we attempt to answer how collaboration strength affects the catch-up of enabling technology in various technology life cycle stage, using a global contrast between innovations in AI and the IC industry, with co-patents as the corpus.

Research question and framework

How can the extent of decentralization in the cooperation networks of a country be measured? Is there a coevolution of network decentralization and technical catch-up and, if so, how? And, whether and how do countries and/or with different network scales vary in catch-up performance? First, we suggest a metric that quantifies the degree of decentralization in a country's collaboration networks, based on Lorenz curves and the Gini coefficient. Second, we explore how, through the stages of development towards technical catch-up, decentralization develops. Third, we explore the links between the size of the cooperation networks of a country and technological catch-up through industries and across countries.

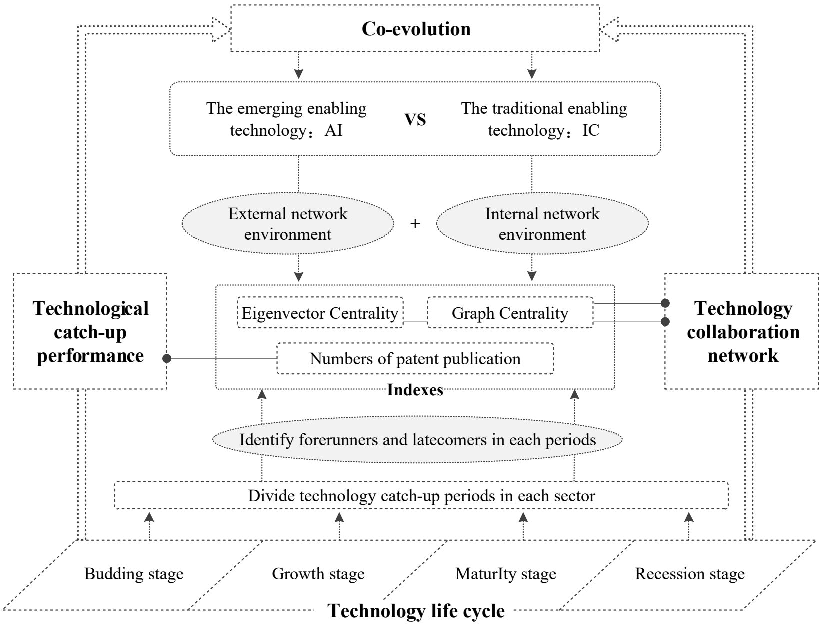

Fig.1 Research framework

In this research framework, we divide the catch-up periods and collaboration network periods in enabling technologies based on technology life cycle, and identify the forerunners and latecomers in each period. And then, this paper constructs the global collaboration network and each country's technology collaboration network in enabling technologies of AI and IC. To exploring their environmental characteristics from external network and internal network, centrality and density indexes are used respectively. As for the measurement of catch-up, this paper attempts to measure technology catch-up based on technology capacity from the quantitative perspective, and patent information is the most accurate and essential reflection of technology innovation (Xue and Jiang, 2019). So, we define the technology catch-up as a country that overtakes other countries' technology innovation capacity, which is measured by the number of patent publication.

The main measurement and indicators we use mainly include:

(1) Degree centrality measurement

Centrality is an efficient indicator for depicting the power and influence of nodes in a network. Degree centrality means the number of nodes connected to a node; it represents the scope of an actor's collaborations, so we chose degree centrality as our index.

(2) Lorenz curve and Gene coefficient

By first ranking the degree centrality for each actor from lowest to highest and then plotting the cumulative fraction of degree centrality (y2) against the cumulative fraction of individual actors (x), we built a Lorenz collaboration network centrality curve (green). This curve's upper limit is y1=x, which indicates perfect equality (purple), although both range from 0 to 1 in theory. The plot is shown in Fig 9. The area between the Lorenz curve and the perfect equality line is quantified by SA, and the area under the Lorenz curve is quantified by SB. The Gini coefficient is SA's ratio to SA's and SB's sum. The smaller the Gini coefficient, the lower the centrality of the degree, i.e., the greater the decentrality of the degree, as shown in fig 3.

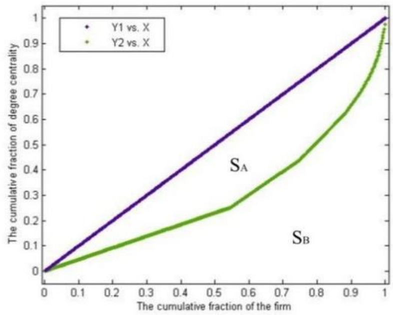

Fig.3 Theoretical illustration of how Lorenz curves and Gini coefficients are calculated

(3) Decentralization measurement

For more accurate curve fitting, this paper used the Power function expression as follows to approximate the Lorenz curve.

$$y=\alpha x^{\beta}$$

To quantify the area of S_B, we used the integration formula

$$\int \alpha x^{\beta} dx = \frac{\alpha}{\beta+1} x^{\beta+1}.$$

The cumulative fraction of the firm (x) ranges from 0 to 1, so the result is

$$S_B = \int_0^1 \alpha x^{\beta} dx = \frac{\alpha}{\beta+1}\left(1^{\beta+1}-0^{\beta+1}\right) = \frac{\alpha}{\beta+1}.$$

The cumulative fraction of degree centrality (y) also ranges from 0 to 1; therefore, the sum value of S_A and S_B must be 0.5, which means the Gini coefficient is calculated by

$$G=\frac{S_A}{S_A+S_B}=\frac{S_A+S_B-S_B}{S_A+S_B}=1-\frac{S_B}{S_A+S_B}=1-2S_B=1-\frac{2\alpha}{\beta+1}.$$

Therefore, the Gini coefficient of how decentralized a country or region's technological collaboration network is can be calculated with

$$D=\frac{1}{G}=\frac{1}{1-2S_B}=\frac{\beta+1}{\beta-2\alpha+1}, G\in(0,1]$$

Preliminary empirical results

We have situated our research on two sectors, the emerging technology AI and the traditional technology IC. To this end, we developed two sets of keywords to use as search terms for patent publication data and collected data from the Derwent World Patents Index (DWPI) database (Jiang and Chen, 2022).

We use Loglet Lab software to complete the model fitting of enabling technology and divide IC & AI into buddying stage, growth stage, maturity stage and recession stage. Based on the above parameters, the technology life cycle curve of AI and IC are drawn in Fig.2. As shown in Fig.2a, buddying stage of AI is

1956~2012, growth stage is 2013~2028, maturity stage is 2029 ~2045, recession stage is after 2045. As shown in Fig.2b, buddying stage of IC is 1965~1998, growth stage is 1999~2012, maturity stage is 2013 ~2027, and recession stage is after 2027.

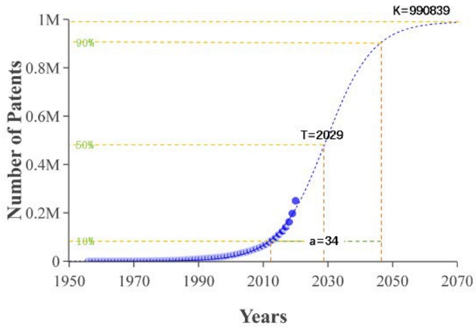

Fig.2a the technology life cycle of AI

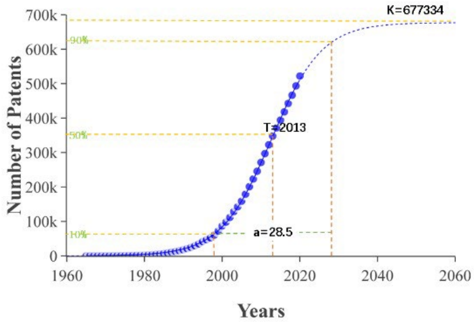

Fig.2b the technology life cycle of IC

As shown in Table 1, fitting the Lorenz curves with MATLAB 7.0 gave us the values for 'α' and 'β' in all the selected countries of the two sectors. We can see that in all the models, the values of the adjusted R-squares were greater than 0.9, suggesting a well-fitting Lorenz curve.

Table 1. The Gini coefficients

	α	β	SSE	RMSE	R-square	Adjusted R-square	Gini coefficient
AI: US-1970-2002	0.838	1.470	0.947	0.035	0.977	0.979	0.322
AI: US-2003-2011	0.867	1.480	1.626	0.035	0.981	0.981	0.3001
AI: US-2012-2017	0.834	1.432	1.763	0.382	0.975	0.975	0.314
AI: CN-1970-2002	0.934	1.096	0.011	0.024	0.993	0.993	0.108
AI: CN-2003-2011	0.838	1.275	0.731	0.034	0.981	0.981	0.263
AI: CN-2012-2017	0.770	1.340	3.764	0.036	0.974	0.974	0.342
AI: JP-1970-2008	0.758	1.951	1.328	0.041	0.965	0.965	0.486
AI: JP-2009-2017	0.805	1.782	0.782	0.037	0.975	0.975	0.421
AI: KR-1970-2008	0.728	1.650	0.747	0.052	0.941	0.941	0.450
AI: KR-2009-2017	0.775	1.671	0.782	0.040	0.968	0.968	0.419
IC: US-1977-1990	0.856	1.356	0.084	0.044	0.971	0.970	0.274
IC: US-1991-2000	0.843	1.610	0.151	0.035	0.980	0.980	0.354
IC: US-2001-2016	0.781	2.194	0.669	0.047	0.955	0.955	0.512
IC: JP-:1977-1990	0.858	1.201	0.039	0.037	0.980	0.979	0.221
IC: JP-1991-2000	0.780	1.780	0.222	0.042	0.965	0.965	0.439
IC: JP-2001-2016	0.737	2.649	0.676	0.050	0.941	0.941	0.596
IC: CN-1977-2008	1.000	1.000	1.000	1.000	1.000	1.000	1.000
IC: CN-2009-2016	0.931	1.160	0.019	0.029	0.990	0.989	0.138
IC: KR-1977-2008	0.911	1.488	0.032	0.040	0.980	0.980	0.268

IC: KR-2009-2016	0.847	1.734	0.055	0.052	0.961	0.959	0.380

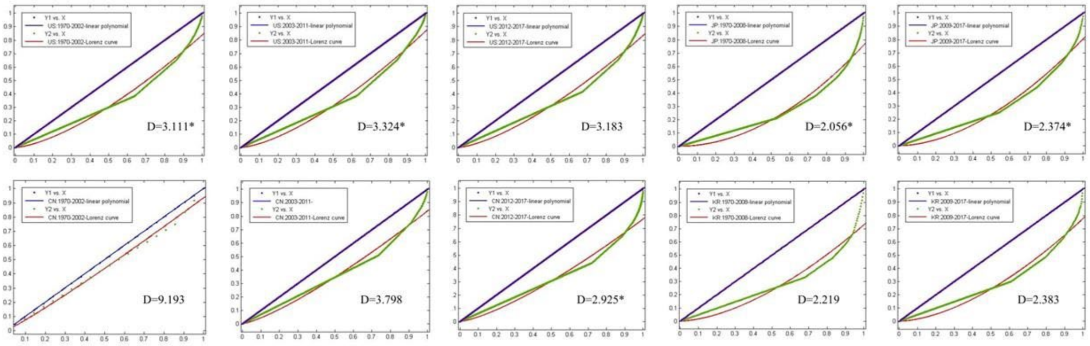

Fig.4 Lorenz curves expressing the decentralization of collaboration networks in the AI industry

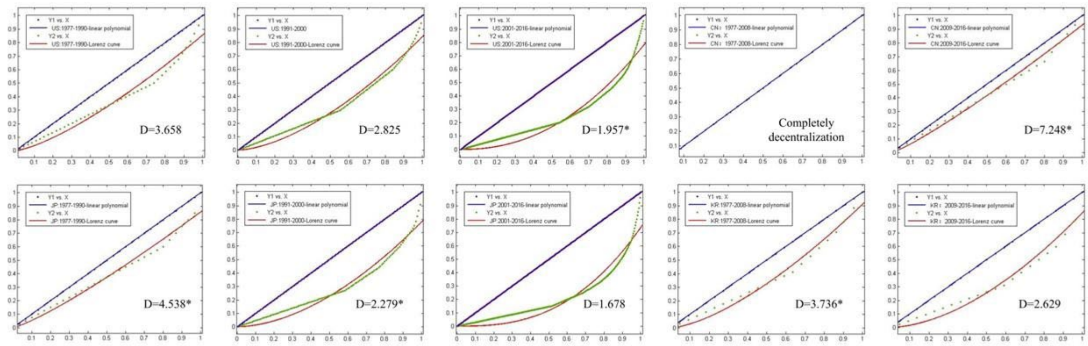

Fig.5 Lorenz curves expressing the decentralization of collaboration networks in the IC industry

Overall, between the two sectors, we see several main differences. First, the scale of collaborations in AI is much larger than in IC. Second, in IC, the number of joint patents is far lower than in AI. It is obvious that AI businesses are more willing to collaborate with each other. Third, for IC, there are far fewer forerunners than for AI on the outer layer of the circle.

From a historical angle, Fig. 4 shows that: a) China's collaborations were more decentralized than the US's in the first two stages of technological catch-up as the latecomer in first-tier AI; and b) China surpassed the US as collaborations coalesced, marking the third stage.

Fig.5 illustrates this same analysis for the IC sector. These tests show that: a) Japan's networks in the first catch-up stage were more decentralized than the US; and b) less decentralized than the US in the last two catch-up stages after the US overtook Japan as the clear leader in the field. Likewise, the trends are in line with the US and Japan for the second-tier leaders, China and South Korea.

Conclusion and Discussion

First, the AI and IC sectors have opposite co-evolution patterns due to their different characteristics of industries and networks. Decentralization and technological catch-up in AI are inversely proportional, which means that networks of forerunner tend to be less decentralized than the latecomers. In contrast, decentralization tends to be directly proportional to the extent of technological catch-up in IC, i.e., forerunners tend to be more decentralized than the latecomers.

Second, there is an obvious decentralization of the first-movers in a country, i.e. the topmost enterprises in sectors. As polycentric patterns in growth are considered to be an important aspect of emerging industries, our findings support this conclusion, showing that the driving effect of the dominant firms in both AI and IC fade as time goes on.

Third, the evolution of decentralization differs between first-tier and second-tier leading countries. For firsttier leading countries, the decentralization trend of collaboration networks is the same– generally decreasing as the industry develops. But, for second-tier leaders, it increases with technological catch-up in AI, while, in the IC industry, it decreases.

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